REGISTRATION OF DSM AND RANGE IMAGES FOR 3-D POSE ESTIMATION OF AN UNMANNED GROUND VEHICLE

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Abstract: In this paper, we propose a new approach which registers a range image which is acquired from a 3-D range sensor to a DSM to estimate the 3-D pose of an unmanned ground vehicle. Generally, 3-D registration is divided into two parts that called as coarse and refinement steps. Above all, a proper feature matching technique is demanded between the DSM and the range image for the coarse registration to register precisely and speedy. We generated signatures using shape parameterization about the DSM and the range images and got a 3-D rigid transformation by matching them to minimize registration error.

1 INTRODUCTION

To achieve duty of an UGV(unmanned ground vehicle), a navigation system is essential to provide information such as the position of the vehicle, travelling speed, and etc. However, high accuracy navigation systems are usually high price so that additional costs are required for operating them. Therefore, in order to account for productivity and an effectiveness of the UGV, a low-priced navigation system is needed. By the way, solutions which revise the navigation error are demanded simultaneously. To overcome this problem, it is necessary to obtain range images using multiplex sensors mounted on the UGV and develop a real-time algorithm which revises the navigation error using a 3-D registration technique with a pre-produced DSM(digital surface model).

The 3-D registration technique is to find a rigid transformation which best fits the data to its corresponding model, i.e., it is a process which transforms 3-D geometrical information such as vertices and surfaces acquired from each private coordinate system into a common coordinate system.

In general, the 3-D registration techniques are divided into two parts that one of them is called as coarse registration which computes an initial estimation of the rigid motion between two clouds of points and the other is called as refine registration which minimizes registration error using the initial estimation. Hence according to the accuracy of the initial estimation, the performance of last registration refinement becomes satisfactory or not.

The key point for the successful coarse registration is to extract appropriate correspondences which have reliability between two objects. There exist a number of the feature extraction methods which can be grouped in two fundamental

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approaches. One of them is 2-D image based extraction that using corners, edges or chromatic information and the other is using 3-D geometrical information such as *surface normal* and *Point fingerprint* (Sun, 2001).

To extract feature points, In (Vandapel, 2006), Nicolas Vandapel et al. used *spin-images* for the terrain model and Soon-Yong Park et al. proposed *SDEBM*(sampled depth edge block matching) using edge information of 3-D model (Park, 2007).

In this paper, we present a new registration technique which can be applied for the 3-D pose estimation of an UGV. For the registration, we generated signatures using shape parameterization about the DSM and the range images and got a 3-D rigid transformation by matching them to minimize registration error.

2 COARSE REGISTRATION BY MATCHING LOCAL SIGNATURE

Because our work is an extension of signature based matching technique, in this section, we review how signatures are generated and used in previous coarse registration cases.

2.1 Signature Matching

Generally, the coarse registration between two 3-D terrain models is accomplished by constructing and matching signature at selected points on both surfaces which are invariant by changes in pose. Correspondences are pair-wised between points with similar signature and after filtering of the correspondences, the Euclidean transformation that registers the two terrain models coarsely is computed by the correspondences. Here is noticeable point that to design appropriate signature which represents invariant characteristic well affects the matching accuracy.

2.2 Image-based Signature

There are many surface representation techniques which used for object matching or recognition. Especially, characterization into a 2-D image by shape parameterization has been one of the most popular methods for surface representation. The *spin-images* algorithm which introduced by Johnson and Hebert in (Johnson, 1999) is a typical application that apply the imaging mechanism to represent the surface shape. They used two factors for generating the signature: radial coordinate α is a distance between the central point and a certain point which is projected into the tangent plane from a neighboring point x and the elevation coordinate β is the signed perpendicular distance to the tangent plane. Using these distances, a signature is generated representing α on the x-axis and β on the y-axis. As another well-known image based signature, there is a *surface signature* that proposed by Yamany and Farag in (Yamany, 1999). The main idea of this approach is to encode the distance and normal variation between a central point and every other feature points in the signature. In similar way to the *spin-images*, a signature is also generated by representing the distance and the normal variation on the x-axis and the y-axis separately.

The main advantage of this image-based signature matching technique comes from compactness and stable. Hence it is possible to perform simple and efficient computation of the similarity of two surfaces patch by comparing the signatures. Considering this advantage, in our research, we aimed at designing a signature that is invariant and can be computed efficiently in the same manner as those registration cases.

3 A NEW APPROACH FOR TERRAIN MAPPING

3.1 KNU Point Signature

Figure 1. shows the fundamental scheme of our approach. The signature image is generated as follows: for a central point $\mathbf{p}$ which is defined by its 3-D coordinates and the normal $\mathbf{n_p}$, each neighboring point $\mathbf{x}$ with its normal $\mathbf{n_x}$ in the support region can be related by

$$KPS(\mathrm{x}) \rightarrow (\alpha, \beta, \gamma\ ) = \left(\|\mathbf{x}-\mathbf{p}\|\ ,\ \mathbf{n_p}\cdot\mathbf{n_x}\ ,\ \frac{\mathbf{n_p}\cdot(\mathbf{x}-\mathbf{p})}{\|\mathbf{x}-\mathbf{p}\|} \right) \quad (1)$$

The α and β are respectively defined as a Euclidean distance and an inner product of the normals between central point and each other points and γ is defined as a direction angle. Like the *spin-image*, we also generated a signature representing α on the x-axis and β on y-axis but the bins are filled up with an accumulation of γ-value whereas the each bin of the *spin-image* contains the number of points that belong to the corresponding region.

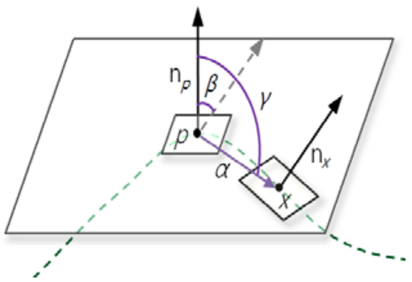


Figure 1: The fundamental scheme of KNU point signature.

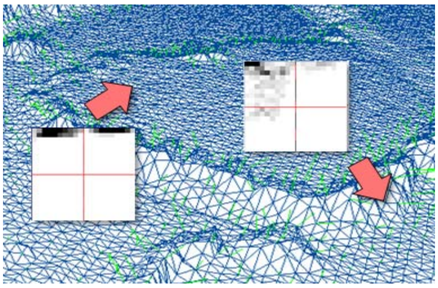


Figure 2: Local terrain characterization.

Since α and β are in real number space, the quantization procedure for generating the images is needed. When the maximum and the minimum value of α and β are given, using definition (2), an image coordinate I can be determined.

$$I(x_i, y_j) = (\alpha_{min} + \frac{\alpha_{max} - \alpha_{min}}{w} i\ ,\ \beta_{min} + \frac{\beta_{max} - \beta_{min}}{\mathrm{h}} j) \quad (2)$$

3.2 Feature Selection Strategy

In general, a terrain data consists of millions of vertices and thus it is not practical to use all of them as candidate features for matching. Especially points in flat area have less useful information for registration. In such regions there is high mutual similarity and finally, operating the UGV's point of view, the facts will affect real-time efficiency of whole system and matching accuracy. Therefore, it is necessary to define features take into account the geometrical attribute of the 3-D shape and the matching algorithm must be performed between the features of the objects to efficiently correlate surface points.

To extract available features, exploring with respect to former territory of the 3-D model, we took fractions of regular size and performed evaluation about flatness, and then the results of the evaluation were saved into an array which called as feature map. As shown in the figure 3, there is a NxN patch on the surface mesh and variance of normals of the vertices at the patch is computed as follows:

$$\overline{V_X} = \frac{1}{N^2} \sum_{e \in W} \left| \|\widehat{V_{X_c}}\| - \|\widehat{V_{X_e}}\| \right| \quad (3)$$
$$\overline{V_Y} = \frac{1}{N^2} \sum_{e \in W} \left| \|\widehat{V_{Y_c}}\| - \|\widehat{V_{Y_e}}\| \right|$$
$$\overline{V_Z} = \frac{1}{N^2} \sum_{e \in W} \left| \|\widehat{V_{Z_c}}\| - \|\widehat{V_{Z_e}}\| \right|$$

$$\sigma_X = \frac{1}{N^2} \sum_{e \in W} \left(\|\widehat{V_{X_e}}\| - \overline{V_X} \right)^2$$
$$\sigma_Y = \frac{1}{N^2} \sum_{e \in W} \left(\|\widehat{V_{Y_e}}\| - \overline{V_Y} \right)^2$$
$$\sigma_Z = \frac{1}{N^2} \sum_{e \in W} \left(\|\widehat{V_{Z_e}}\| - \overline{V_Z} \right)^2$$

$(V_{X_c}, V_{Y_c}, V_{Z_c})$ is central point's 3-D coordinates of the patch. After measuring the variance, using definition (4), the patch can be classified as a good or a bad feature.

$$\varepsilon = \sqrt{{\sigma_X}^2 + {\sigma_Y}^2 + {\sigma_Z}^2} \quad (4)$$
$$\varepsilon > threshold$$

Once a classification had been achieved, the result will be saved into a cell of the feature map. After this, the feature map will be referenced at run-time matching.

3.3 Signature Matching

The main purpose of this step is to establish a set of correspondences between the DSM and the range data. All signatures have same image size so that the general template matching method such as SSD(sum of squared differences), SAD(sum of absolute distance) and NCC(normalized correlation coefficient) can be used as a matching solution. For the matching, we used the NCC. Let P be one of range data's signature and Q be one of the DSM's signature. Then the correlation coefficient $R(P, Q)$ is calculated by

$$R(P,Q) = \left| \frac{\frac{1}{N_D} \sum_{i \in D} (p_i - \bar{p})(q_i - \bar{q})}{S \cdot S'} \right| \quad (5)$$

N_D is the total number of pixels in the domain D which is defines over the signature image size. When R is high, the signature P and Q are similar and when R is low, they are not similar.

In terrain matching scenario, comparing signature directly without any restriction often drops the real-time efficiency. Hence, we applied search range as a constraint to perform the matching algorithm. In this paper, the search range is specified by $\pm$25m in position of the UGV.

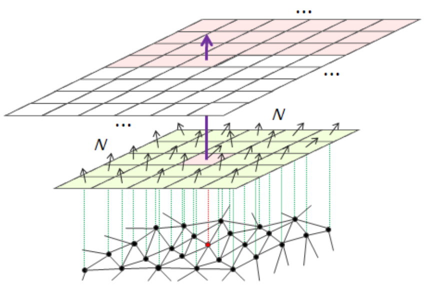


Figure 3: Feature map construction.

4 EXPERIMENTAL RESULT

The experiment was performed with the assumption that an UGV is moving on the field and a sequence of range images are obtained continuously from a range sensor. The range sensor has 45 degree of field of view and the sensing distance is from 50m to 1km and the range image's resolution is 128x128. At this point in time, because of absence of real range data, we have simulated the scenario using OpenGL.

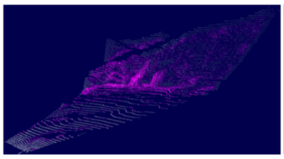
After estimating initial transformation, for refinement, we used *ICP* algorithm (Besl, 1992) which is widely used for minimizing registration error. Since original *ICP* algorithm has time consuming problem, we applied *kd-tree* algorithm to speed-up the *ICP* and the iteration count for *ICP* was selected by 50.

Figure 4 shows the results of the registration process in order of precedence. Many features are found at the bush of the ridge and the boundary between the mountain and the field (fig. 4-a) and through uniform sampling, the best candidates for matching were selected (fig. 4-b, 4-c). After matching process, the correspondences also established appropriately (fig. 4-d). Finally, we could notice that the range image was fitted into the DSM(fig. 4-e).

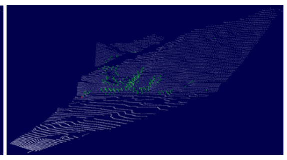
Table 1. provides timing information and details on the registration process. As expected, the matching step keeps the most of registration time.

Table 1: Registration Statistics.

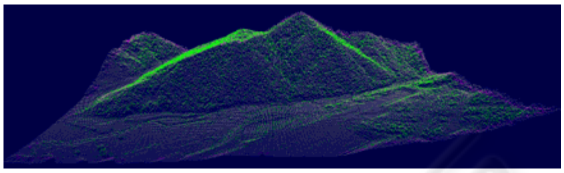
Step	Average time (sec)
Feature selection	0.033
Signature generation	0.001
Matching the correspondences	3.157
Initial transformation estimation	0.489
ICP using *kd-tree* (50 times iter.)	0.193



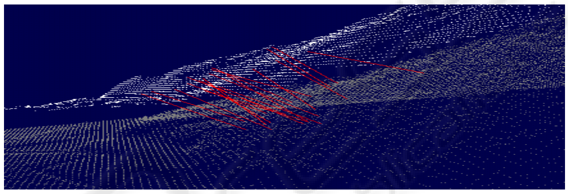
(a) Feature extraction



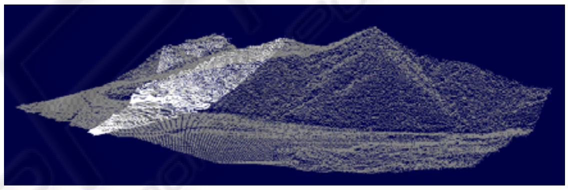
(b) Sampled features of a range image



(c) Sampled feature of the DSM



(d) A set of correspondences



(e) The result of registration

Figure 4: The total procedure of our approach.

5 CONCLUSIONS

In this paper, we have described registration technique for 3-D pose estimation of an unmanned ground vehicle. Using a signature which includes 3-D geometrical characteristic by shape parameter-zation, a set of correspondences can be established and used for the coarse registration.

In future work, we intend to conduct a more thorough analysis on the registration performance and through coupling with the 2-D based feature extraction method, we would like to improve the registration performance.

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REFERENCES

Sun, Y., Abidi, M., 2001, Surface matching by 3d point's fingerprint, *Proc. Of 8th Int. Conf. Computer Vision (ICCV)*, pages 263-269

Vandapel N., Donamukkala, R., R., Hebert, M., 2006, *The International Journal of Robotics Research*, Vol. 25, No. 1, pp. 31-51.

Park, S., Baek, J., 2007. Online Multi-view Image Registration using Geometric and Photometric Feature Tracking, *The 6th international Conference on 3-D Digital Imaging and Modeling*.

Johnson. A., Hebert, M., 1999. Using spin images for efficient object recognition in cluttered 3d scenes, *IEEE TPAMI*, 21(5): 433-449

Yamany, S., Farag, A., 1999. Free-form surface registration using surface signatures. *Proc. of 7th Int. Conf. Computer Vision (ICCV)*, pages 1098–1104.

Besl, P., McKay, N. 1992. A method for registration of 3-D shapes, *IEEE Trans. Pattern Anal. Mach. Intell*. 14 (2): 239-256